ENERGY TRADING IN SMART MICROGRIDS

Dissertation submitted to
Visvesvaraya National Institute of Technology, Nagpur
in partial fulfillment of the requirements for the award of
the degree

Master of Technology
in
Computer Science & Engineering

by

SHIVAM KR SINGH (MT23MCS022)

under the guidance of

Dr. M. P. Kurhekar

Department of Computer Science & Engineering
Visvesvaraya National Institute of Technology
Nagpur 440 010 (India)

JUNE 2025

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Department of Computer Science & Engineering
Visvesvaraya National Institute of Technology, Nagpur

Declaration

I, **Shivam Kumar Singh**, hereby declare that this dissertation titled **" Energy Trading in Smart Microgrids "** is carried out by me in the Department of Computer Science & Engineering of Visvesvaraya National Institute of Technology, Nagpur. The work is original and has not been submitted earlier whole or in part for the award of any degree at this or any other Institution.

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ABSTRACT

As renewable energy becomes more widespread and power systems shift from centralized to distributed networks, microgrids have emerged as crucial building blocks of modern energy infrastructure. Yet managing power allocation across interconnected microgrids remains a challenging puzzle - how do you efficiently distribute electricity from multiple sources to various consumers while keeping costs low, meeting demand, and maintaining system reliability, all in real-time?

This research tackles a significant gap in our understanding by comparing five different approaches to solving this power allocation problem: two nature-inspired algorithms (Particle Swarm Optimization and Ant Colony Optimization), a fairness-focused Priority-Based Round-Robin method, a novel Dynamic Rating-Based system that learns from past consumption patterns, and Dynamic Price Adjustment mechanisms that respond to supply-demand imbalances. We tested these algorithms using realistic data from RAPSim simulations across five different microgrid setups, each with its own unique challenges.

Our approach works in two stages: first, each microgrid optimizes its internal power distribution, then microgrids trade excess power with each other when needed. We measured performance using three key metrics - how well consumer demand was satisfied, how cost-effective the allocation was, and an overall efficiency score that balances both factors.

The results were quite surprising. Contrary to what most researchers expected, the simpler heuristic approaches actually outperformed the complex nature-inspired algorithms in almost every way. Our Dynamic Rating-Based algorithm came out on top, satisfying 98.77% of consumer demand with excellent cost efficiency and completing its calculations in just 0.10 seconds. The Priority-Based Round-Robin approach performed

nearly as well, achieving 98.72% satisfaction with remarkable consistency across different conditions.

The nature-inspired algorithms, while popular in academic literature, showed significant weaknesses. PSO managed 98.48% satisfaction but was the most expensive option and took nearly six times longer to run. ACO was even more problematic - while it could achieve near-perfect results under ideal conditions, it sometimes failed catastrophically, dropping to just 85.11% satisfaction when conditions became challenging.

We introduced several innovations, including a rating system that prioritizes consumers based on their recent usage patterns, an automatic pricing mechanism for energy trading that finds mutually beneficial prices, and a multi-phase allocation process that balances efficiency with fairness. Our statistical analysis across all test scenarios confirmed these findings were significant and reliable.

Perhaps most importantly, we discovered that algorithm performance varies dramatically depending on the specific characteristics of each microgrid. Some algorithms showed performance drops of up to 15% when conditions became difficult, highlighting the need for careful algorithm selection based on real-world operating conditions.

These findings have immediate practical value for anyone designing or operating microgrid systems. Our results suggest that simpler, more reliable algorithms that can make decisions in fractions of a second are often better choices than complex optimization methods that take longer and may be less reliable when it matters most.

This research advances the field by providing the first comprehensive comparison of different optimization approaches specifically for microgrid power allocation, introducing new methods for fair and efficient power distribution, and offering practical guidelines for choosing the right algorithm based on specific system needs. Future research should explore combining the reliability of simple methods with the optimization potential of more complex approaches, and develop smart systems that can automatically choose the best algorithm for current conditions.

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Chapter 1

Introduction

1.1 Background and Motivation

The global energy landscape is undergoing a major transformation as societies shift from centralized fossil fuel-based power systems to distributed renewable energy networks. At the center of this change are microgrid systems - localized electrical networks that can work independently or alongside the main electrical grid. These systems bring together different energy sources like solar panels, wind turbines, battery storage, and conventional generators to serve local communities, industrial facilities, or commercial areas. The growing use of microgrids is driven by their ability to enhance energy security, improve efficiency, reduce environmental impact, and provide reliable power during grid outages.

However, operating microgrid systems effectively presents complex optimization challenges that have become more critical as these systems grow and connect with each other. The main challenge is efficiently allocating power from multiple sources to multiple consumers while meeting competing goals: minimizing costs, maximizing demand satisfaction, ensuring reliability, and maintaining fair access to energy resources. This multi-objective optimization problem becomes much more complex when dealing with interconnected microgrid networks, where power trading between microgrids adds variables related to transmission losses, pricing, and coordination between grids.

Traditional centralized power systems use well-established economic dispatch algorithms and market mechanisms that have been developed over decades. However, these

approaches do not work well for the distributed, dynamic, and often independent nature of microgrid operations. Microgrids need to make real-time allocation decisions based on rapidly changing renewable energy production, variable consumer demands, storage system conditions, and external grid situations. Additionally, integrating multiple stakeholders with different priorities - including individual consumers, microgrid operators, and neighboring grids - requires sophisticated algorithms that can balance efficiency with fairness.

The economic consequences of poor power allocation in microgrids are significant. Inefficient allocation can cause higher operational costs, reduced system lifetime through improper resource use, and lower consumer satisfaction due to unmet demand. Additionally, as microgrids become essential infrastructure for communities and businesses, the reliability and predictability of allocation algorithms become crucial for maintaining social and economic stability.

1.2 Problem Statement

This research addresses the optimization of power allocation in interconnected microgrid systems through comparative evaluation of multiple algorithmic approaches. The core challenge involves distributing available power from multiple sources to consumers across interconnected microgrids while simultaneously maximizing demand satisfaction, minimizing operational costs, and optimizing system efficiency.

The problem operates under strict constraints: physical capacity limits, consumer demand boundaries, transmission losses, and non-negativity requirements. Additional complexities include multi-scale decision making, dynamic pricing mechanisms, temporal dependencies, and fairness considerations across consumer types.

Real-time operational requirements demand allocation decisions within seconds, eliminating computationally intensive traditional optimization methods. Current research lacks comprehensive comparative analysis between meta-heuristic and heuristic approaches, particularly regarding optimization quality versus computational efficiency trade-offs across diverse microgrid configurations.

1.3 Research Objectives

This research addresses identified gaps in microgrid power allocation optimization through comprehensive objectives spanning algorithm development, performance evaluation, and practical implementation.

The first objective involves developing and implementing a comprehensive suite of diverse power allocation algorithms representing different optimization paradigms: metaheuristic approaches (PSO and ACO), deterministic heuristic methods (Priority-Based Round-Robin and Dynamic Rating-Based allocation), and economic mechanism design (Dynamic Price Adjustment algorithms).

The second objective conducts systematic comparative analysis across multiple performance dimensions: quantitative performance (demand satisfaction rates, cost efficiency, composite metrics), computational efficiency (execution time, memory utilization, scalability), and reliability assessment (performance consistency across diverse conditions).

The third objective evaluates algorithm performance using realistic microgrid data through multi-microgrid network simulation, time-series analysis across operational periods, and stress testing under challenging supply-demand conditions.

The fourth objective systematically analyzes trade-offs between competing optimization goals: cost optimization versus demand satisfaction, computational efficiency versus solution quality, and individual fairness versus system-wide efficiency.

The fifth objective develops evidence-based recommendations for algorithm selection and parameter optimization, including condition-based selection criteria, performance prediction models, and implementation best practices.

The sixth objective introduces novel mechanism design approaches: dynamic rating systems based on historical consumption patterns, sweet point pricing mechanisms for bilateral energy trading, and multi-phase allocation processes balancing efficiency and fairness.

1.4 Research Contributions

This research makes several significant contributions to the field of microgrid optimization and energy management:

1.4.1 Theoretical Contributions

Comprehensive Algorithmic Framework: This work establishes the first systematic comparison of diverse optimization paradigms for microgrid power allocation, ranging from traditional meta-heuristic algorithms to novel heuristic approaches. The comprehensive evaluation framework provides a foundation for future research in this rapidly evolving field.

Dynamic Rating-Based Optimization: Introduction of a novel consumer rating mechanism that dynamically prioritizes power allocation based on historical consumption patterns. This approach bridges the gap between fairness considerations and efficiency optimization by incorporating temporal equity into allocation decisions.

Multi-Phase Allocation Methodology: Development of a structured approach that separates internal microgrid optimization from inter-microgrid trading, allowing for specialized optimization techniques at each level while maintaining system-wide coordination.

1.4.2 Practical Contributions

Performance Hierarchy Establishment: Empirical evidence establishing that heuristic approaches can outperform traditional meta-heuristic algorithms in both optimization quality and computational efficiency for practical microgrid applications. This finding challenges conventional assumptions in the field and provides new directions for algorithm development.

Real-time Implementation Framework: Development of algorithms specifically designed for real-time operation with execution times suitable for practical deployment (0.10-0.58 seconds), addressing a critical gap between theoretical optimization and practical implementation requirements.

Economic Mechanism Innovation: Introduction of sweet point pricing mechanisms that automatically determine mutually beneficial trading prices in bilateral energy markets, reducing transaction costs and enabling efficient market clearing without complex bidding processes.

1.4.3 Methodological Contributions

Standardized Evaluation Metrics: Establishment of comprehensive performance metrics that balance multiple optimization objectives, including the novel Efficiency-Fairness Score (EFS) that combines satisfaction and cost considerations into a single comparative measure.

Statistical Validation Framework: Implementation of rigorous statistical analysis methods to validate algorithm performance and establish confidence intervals for comparative results, ensuring the reliability and reproducibility of findings.

Scalability Assessment: Systematic evaluation of algorithm scalability and computational requirements, providing practical guidance for system designers regarding hardware requirements and performance expectations.

1.5 Research Methodology Overview

This research employs a comprehensive experimental methodology combining theoretical algorithm development with empirical validation using realistic microgrid data. The methodology is structured around four key phases:

1.5.1 Algorithm Development Phase

The research begins with the systematic development of five distinct algorithmic approaches, each representing a different optimization paradigm. The Particle Swarm Optimization (PSO) and Ant Colony Optimization (ACO) implementations leverage established meta-heuristic frameworks adapted specifically for the microgrid power allocation problem. These algorithms employ population-based search strategies with carefully tuned parameters to explore the complex solution space.

In contrast, the Priority-Based Round-Robin algorithm introduces a deterministic approach that ensures temporal fairness through a rotating priority queue system. The Dynamic Rating-Based algorithm advances this concept by incorporating historical consumption patterns, dynamically prioritizing consumers based on their recent usage relative to historical maximums. Finally, the Dynamic Price Adjustment mechanisms introduce economic signals that reflect resource scarcity, implementing three distinct pricing formulas to balance supply and demand.

All algorithms implement a consistent two-stage process: internal allocation within each microgrid followed by inter-microgrid trading when necessary. This hierarchical approach promotes self-sufficiency while enabling system-wide optimization, and comprehensive constraint enforcement ensures physically feasible solutions that respect source capacities and consumer demands.

1.5.2 Experimental Design

The experimental framework evaluates all algorithms across five distinct microgrid configurations, each presenting different operational challenges and characteristics. This multi-environment testing approach ensures that performance assessments capture algorithm behavior across diverse conditions rather than optimizing for specific scenarios.

Performance evaluation employs three primary metrics: Demand Satisfaction Rate (DSR) measuring the percentage of consumer demand successfully allocated, Cost Minimization Factor (CMF) representing the cost per unit of allocated power, and the Efficiency-Fairness Score (EFS) providing a composite metric that balances satisfaction and cost considerations. The EFS metric uses weighted components (40% satisfaction, 60% cost efficiency) reflecting the practical importance of cost optimization while maintaining adequate demand satisfaction.

1.5.3 Validation and Analysis

Statistical validation ensures the reliability and significance of comparative results through rigorous analysis of performance variance, confidence intervals, and consistency measures. The research employs both quantitative performance analysis and qualitative

assessment of algorithm behavior under stress conditions.

Computational performance analysis evaluates execution time, memory utilization, and scalability characteristics to assess practical implementation feasibility. This analysis is particularly critical for real-time applications where allocation decisions must be computed rapidly to respond to changing conditions.

1.6 Thesis Organization

This thesis is organized into five comprehensive chapters that systematically present the research development, implementation, and validation:

Chapter 1: Introduction establishes the research context, motivation, and objectives. It provides essential background on microgrid systems and power allocation challenges, formally defines the research problem, and outlines the key contributions and methodology.

Chapter 2: Literature Review presents a comprehensive survey of existing approaches to microgrid optimization and power allocation. This chapter identifies gaps in current research, establishes the theoretical foundation for the proposed approaches, and positions this work within the broader context of energy management research.

Chapter 3: Methodology provides detailed descriptions of all five algorithmic approaches developed in this research. Each algorithm section includes mathematical formulations, implementation details, parameter selection rationale, and complexity analysis. The chapter also describes the experimental framework, performance metrics, and validation procedures.

Chapter 4: Results and Discussion presents comprehensive experimental results and comparative analysis. This chapter includes quantitative performance evaluation across all algorithms and microgrid configurations, statistical validation of results, computational performance analysis, and detailed discussion of findings with implications for practical implementation.

Chapter 5: Conclusion and Future Work summarizes key findings, discusses their implications for the field of microgrid optimization, and identifies promising directions for future research. The chapter also addresses limitations of the current work and provides

recommendations for practical implementation.

Each chapter builds systematically on previous content, creating a coherent narrative that guides readers from the initial problem motivation through the complete research development and validation process. The comprehensive approach ensures that both theoretical contributions and practical implications are thoroughly addressed, making this work valuable for both researchers and practitioners in the field of microgrid optimization and distributed energy management.

Chapter 2

Literature Review

2.1 Introduction

The optimization of power allocation in interconnected microgrid systems has emerged as a critical research area, driven by the increasing penetration of renewable energy sources and the need for efficient energy management strategies. This literature review examines the current state of research in microgrid power allocation, focusing on optimization algorithms, demand response mechanisms, and peer-to-peer (P2P) energy trading. The review encompasses recent developments from 2022-2025, highlighting the evolution of optimization techniques and their application to complex microgrid scenarios.

Modern utility grids are transitioning from centralized generation structures to distributed and decentralized structures [20]. Microgrids (MGs) provide a clean, efficient, and economical way of integrating renewable energy sources and loads to the main grid [20]. However, significant gaps remain between theoretical advances and practical implementation, particularly in P2P energy trading via public power networks [28].

2.2 Microgrid Energy Management Fundamentals

2.2.1 Architecture and Control Systems

A microgrid uses distributed generations and information technology to create a widely distributed automated energy delivery network [23]. The hierarchical control struc-

ture consists of three levels: primary control (milliseconds via droop control), secondary control (voltage-frequency restoration), and tertiary control (optimal operation via MG central controller) [24].

Smart energy management systems perform real-time energy forecasting of renewable resources, energy storage and controllable loads to minimize total operating costs [11]. The integration of smart grids with microgrids enhances real-time monitoring, control, and optimization through advanced communication technologies [21].

2.2.2 Peer-to-Peer Energy Trading Paradigm

P2P energy trading represents a paradigm shift from centralized energy markets to decentralized, direct trading between prosumers and consumers. [14] noted that P2P trading enables direct transactions between energy producers and consumers, particularly benefiting rural areas with limited centralized electricity access. [28] identified three major implementation challenges: regulatory frameworks, technical infrastructure requirements, and economic viability.

2.3 Optimization Algorithms for Power Allocation

2.3.1 Metaheuristic Optimization Approaches

Particle Swarm Optimization (PSO)

PSO has gained significant attention due to its effectiveness in handling complex, multi-dimensional microgrid problems [5]. [3] demonstrated PSO's effectiveness for managing hybrid renewable energy microgrids under uncertainty, achieving 58% increase in grid electricity sales on clear days and 153% on partially overcast days. [8] developed multi-objective PSO for household microgrids, addressing concentrated power consumption during low electricity price periods while maintaining system reliability.

Ant Colony Optimization (ACO)

ACO has emerged as a powerful alternative for microgrid optimization. [10] demonstrated ACO's effectiveness in reducing operational costs and enhancing system reliabil-

ity, achieving average solution costs of $281.1 compared to $288.5 for competing algorithms. [25] developed scenario-based stochastic frameworks using mixed-integer distributed ACO for handling uncertainty in islanded microgrids.

Hybrid and Advanced Approaches

Recent research emphasizes hybrid metaheuristic approaches combining multiple optimization techniques. [15] revealed that while heuristic optimization mechanisms show promise, local minima and inability to find global optimum create errors in non-linear optimization. [17] developed multi-objective energy management using iterative map-based self-adaptive crystal structure algorithms for renewable and EV-integrated microgrids.

[12] demonstrated PSO's superiority over ACO and genetic algorithms, achieving 80% renewable energy penetration and 15% operating cost reduction.

2.3.2 Advanced Mathematical Programming

Adaptive Penalty Mechanisms

[27] proposed a novel adaptive penalty mechanism (APM) for P2P energy trading that uses three-dimensional penalty systems with deviation percentage factors to reduce excessive penalty rates. The APM balances cost-effectiveness and regulation through real-time monitoring, distributed clearing algorithms, and energy storage integration.

Deterministic Scheduling

Traditional deterministic approaches like round robin scheduling continue to play important roles [13]. [1] developed modified approaches ensuring fairness in power allocation by distributing power thresholds to individual consumers while implementing brownout mechanisms to mitigate blackouts.

2.4 Dynamic Pricing and Demand Response

2.4.1 Real-Time Pricing Strategies

Dynamic pricing has become critical for supply-demand balancing in microgrids. [22] developed advanced optimization using price-elastic demand response with four models (exponential, hyperbolic, logarithmic, and critical peak pricing), demonstrating significant economic and environmental efficiency improvements.

[16] developed dynamic price-based schemes for time-based demand response programs, studying seven types of flexible resources and responsive loads in ramping management. [2] created optimal adaptive control strategies using PSO-based super twisting sliding mode controllers for real-time energy balancing through dynamic pricing.

2.4.2 Smart Grid Integration

[7] emphasized that demand-side management enables communication between energy suppliers and consumers, reducing costs through continuous monitoring and appliance scheduling. [18] highlighted that Multi-Energy Microgrids represent integrated systems delivering optimal sustainable energy solutions.

[4] presented comprehensive strategies for optimizing microgrid load fluctuations through dynamic pricing and electric vehicle flexibility using time-of-use pricing and tiered carbon pricing systems.

2.5 Practical P2P Energy Trading Implementation

2.5.1 Market Mechanisms and Challenges

Despite extensive research, P2P energy trading faces substantial implementation barriers. [28] conducted comprehensive analysis of practical challenges based on a North Wales case study, identifying three primary regulatory problems:

1. Network charging regulations not reflecting actual network usage
2. Lack of incentives for local power balancing

3. Inadvertent promotion of private power networks leading to potential ”death spiral” effects

[26] demonstrated that P2P trading improves local energy generation-consumption balance, with increased diversity of generation and load profiles further facilitating balance.

2.5.2 Technology Integration

Blockchain and IoT technologies are crucial for enabling P2P energy trading [14]. Blockchain provides distributed ledger technology for transparent, secure transactions, while IoT enables real-time monitoring and control of distributed energy resources.

[9] compared GridLAB-D and RAPSim simulation tools, finding significant differences in weather simulation and load modeling that affect reproducibility across simulators, highlighting the need for standardized simulation approaches.

2.6 Energy Storage Integration

Battery energy storage systems have become integral to modern microgrid operations. [6] assessed residential microgrid reliability using genetic and ant colony algorithms, addressing renewable energy variability, storage limitations, and demand fluctuations.

[2] demonstrated superior performance of PSO-STSMC-based models compared to traditional PID, PI, PD, and fractional order controllers for energy storage management. Advanced control systems offer robust performance under varying operating conditions and renewable energy intermittency.

2.7 Research Gaps and Future Directions

2.7.1 Current Limitations

Despite significant advances, several gaps remain. Many approaches suffer from real-time implementation limitations, scalability issues, and multi-objective integration

challenges [2]. The gap between academic research and practical implementation is particularly pronounced in P2P energy trading, with little large-scale commercial deployment globally [28].

2.7.2 Emerging Trends

Recent research focuses on several key areas:

AI/ML Integration: [21] demonstrated machine learning-based energy management and power forecasting in grid-connected microgrids with multiple distributed energy sources, showing promise for addressing complex, dynamic system behavior.

Blockchain and IoT Integration: [14] highlighted these as cutting-edge research areas providing distributed ledger capabilities and smart energy platforms for renewable energy management.

Standardization and Modularity: The evolution toward modular, repeatable systems represents important trends for faster adoption [19].

Multi-objective Optimization: Emphasis on balancing efficiency and fairness in P2P energy trading, moving beyond pure cost optimization to consider equity among participants.

Future research should focus on hybrid optimization approaches, real-time adaptive algorithms, uncertainty management, scalability solutions, and interoperability standards to bridge the theory-practice gap.

2.8 Conclusion

This literature review reveals that microgrid power allocation optimization is rapidly evolving with significant advances in theoretical approaches and practical implementations. The dominance of metaheuristic algorithms, particularly PSO and ACO, demonstrates their effectiveness in handling complex, multi-objective optimization problems. However, significant barriers exist for real-world deployment, particularly in P2P energy trading via public networks.

Key findings include: (1) algorithmic maturity in metaheuristic approaches with increasing hybrid sophistication, (2) substantial practical implementation gaps due to reg-

ulatory, technical, and economic challenges, (3) promising technology integration opportunities through blockchain, IoT, and AI/ML, (4) evolving market structures emphasizing fairness and equity, and (5) critical need for standardized simulation and implementation approaches.

Future success requires holistic approaches combining algorithmic innovation with practical implementation considerations. The integration of AI/ML techniques with traditional optimization methods, coupled with supportive regulatory frameworks and standardized approaches, presents the most promising avenue for advancing toward widespread practical deployment. Close collaboration between researchers, practitioners, and policymakers is essential to address the multi-faceted challenges and realize the full potential of microgrid optimization and P2P energy trading in supporting global sustainable energy transitions.

Chapter 3

Methodology

3.1 Dataset and Experimental Setup

3.1.1 Introduction

This section presents the experimental framework that we developed for evaluating power allocation algorithms in interconnected microgrid systems. The research utilizes the RAPSim (Renewable Alternative Power Simulation) software to generate realistic operational data across five distinct microgrid configurations. This section details the simulation environment, dataset characteristics, temporal analysis patterns, and technical implementation specifications that form the foundation of our comparative algorithm evaluation. The framework allows us to test how different algorithms perform under various operating conditions and provides a foundation for comparing their effectiveness.

3.1.2 RAPSim Simulation Environment

Simulation Platform Overview

We conducted our experiments using RAPSim (Renewable Alternative Power Simulation) software, which is a visual simulation tool that was built specifically for studying renewable energy systems and microgrid optimization. RAPSim offers a user-friendly graphical interface that makes it relatively easy to model different renewable energy sources, electricity consumers, and how they interact with each other across multiple connected microgrids. The software allows researchers to test various situations and observe how

energy flows between microgrids under different real-world conditions.

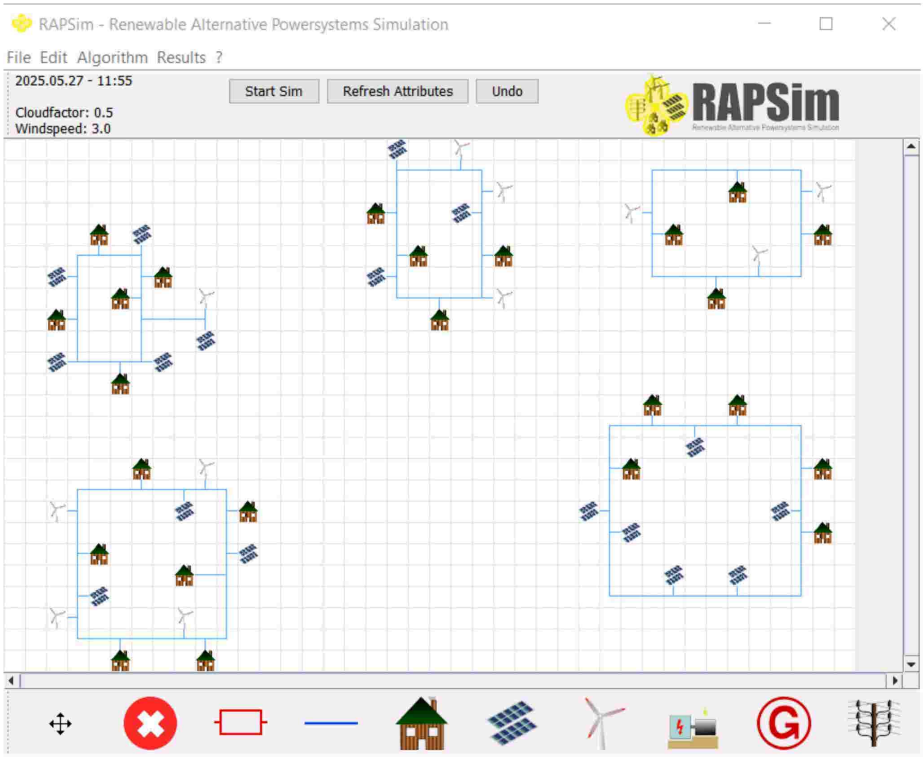

Figure 3.1: RAPSim Simulation Interface Showing Five Interconnected Microgrids with Distributed Energy Resources and Consumer Loads. The interface displays five distinct microgrid areas (bounded by blue rectangles) containing consumer buildings (house icons), solar panels (blue rectangular icons), and wind turbines (white turbine icons).

Visual Simulation Environment

The RAPSim interface shows a simulation with five separate microgrids. Each microgrid contains houses that use electricity, solar panels that generate power from sunlight, and wind turbines that produce power from wind. Power lines connect all microgrids so they can share electricity with each other when needed.

3.1.3 Microgrid System Configuration

Network Architecture Overview

We set up the simulation with five microgrids, and each one had its own configuration that we designed to create different operating situations. Every microgrid has different renewable energy sources mixed together - this way we could see how our algorithm would handle things when the supply and demand kept changing.

Table 3.1: Microgrid Configuration Summary

Microgrid	PV Panels	Wind Turbines	Generation Profile
Microgrid 1	5	1	Deficit periods
Microgrid 2	3	4	Consistent surplus
Microgrid 3	4	3	Surplus generation
Microgrid 4	0	3	Wind-only surplus
Microgrid 5	6	0	Diurnal variation

3.1.4 Network Topology and Connectivity Analysis

Inter-Microgrid Distance Matrix

The way the microgrids are arranged in the simulation interface lets us calculate realistic transmission distances between them, which is important for figuring out transmission losses and what it costs to trade energy. You can see the network layout in Figure 3.2 along with the actual distance measurements we used. This spatial setup is crucial because in real life, the further apart microgrids are, the more energy you lose during transmission - and that affects whether trading makes economic sense or not.

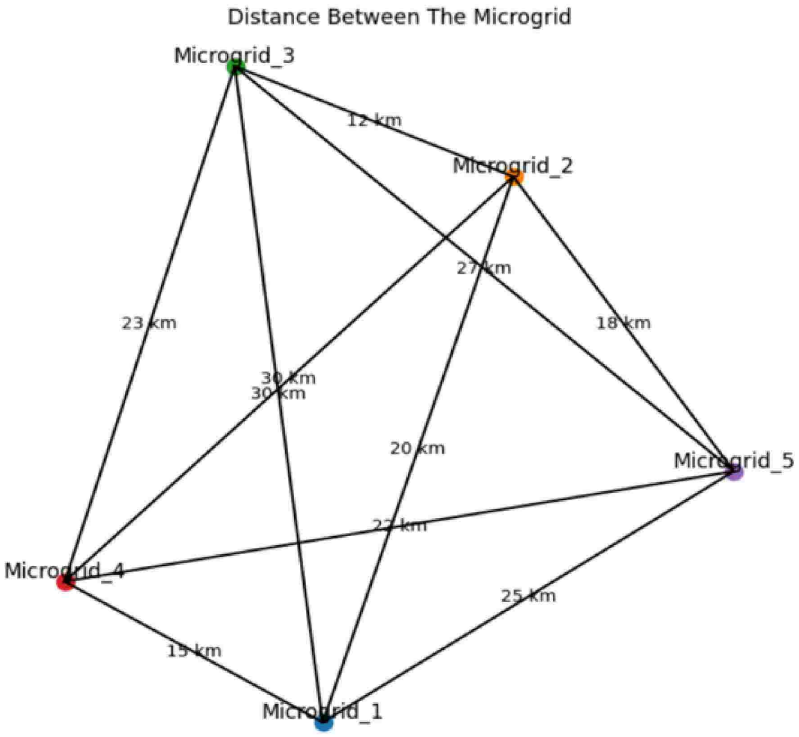

Figure 3.2: Inter-Microgrid Distance Network Topology showing connection distances between all five microgrids in kilometers

Table 3.2: Inter-Microgrid Distance Matrix (km)

	MG1	**MG2**	**MG3**	**MG4**	**MG5**
MG1	0	20	30	15	25
MG2	20	0	12	30	18
MG3	30	12	0	23	27
MG4	15	30	23	0	22
MG5	25	18	27	22	0

Network Topology Characteristics

Distance measurements indicate key microgrid network characteristics: MG2-MG3 represents the shortest connection at 12 km enabling efficient power trading, while MG2-MG4 represents the longest at 30 km with highest transmission losses. MG1 demonstrates central hub potential with balanced distances to all nodes, and two proximity clusters emerge: MG2-MG3 (12 km) and MG1-MG4 (15 km).

3.1.5 Temporal Demand-Production Analysis

Time-Series Data Overview

The RAPSim simulation provided detailed time-series data showing how supply and demand changed across all five microgrids from February 2023 to February 2024. Looking at this data over time, each microgrid configuration shows distinct operating patterns.

Individual Microgrid Temporal Patterns

Microgrid 1

Figure 3.3: Microgrid 1: Demand vs Production Over Time

Microgrid 1 has decent alignment between what it produces and what it needs - production can hit 2,100 kW while demand averages around 917 kW (though it peaks at 1,699 kW and drops to 226 kW, with a standard deviation of 355.64 kW). Still, there are times when it does not produce enough and has to pull power from the other microgrids. This happens often in the evening through midnight when people are using more electricity.

Microgrid 2

Figure 3.4: Microgrid 2: Demand vs Production Over Time

Microgrid 2 shows substantial surplus generation with production averaging 2,538.11 kW (peak: 3,568.93 kW, minimum: 1,421.16 kW, std dev: 586.70 kW) that consistently exceeds demand averaging 959.84 kW (peak: 1,773.33 kW, minimum: 256.43 kW, std dev: 365.46 kW). The wind-heavy setup gives it stable export capacity with almost continuous power surplus, making it the main supplier for trading between microgrids.

Microgrid 3

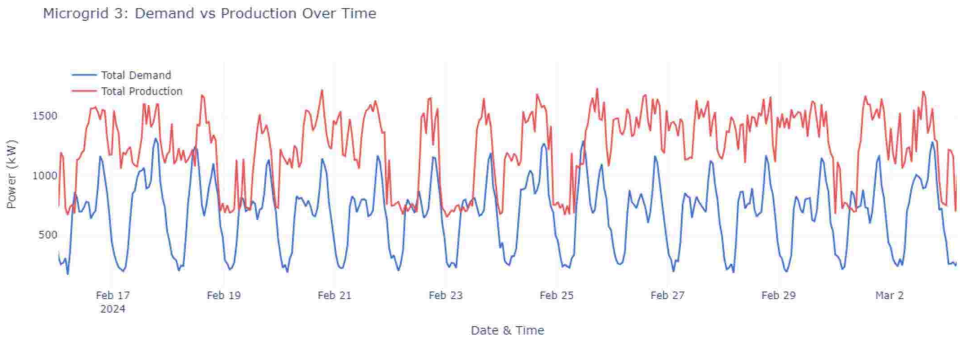

Figure 3.5: Microgrid 3: Demand vs Production Over Time

Microgrid 3 has a balanced generation setup with moderate surplus, where production averaging 1,275.21 kW (peak: 1,873.69 kW, minimum: 651.54 kW, std dev: 302.53 kW) exceeds demand averaging 710.83 kW (peak: 1,316.72 kW, minimum: 150.14 kW, std dev: 276.70 kW). It provides secondary export capacity with good reliability through its solar-wind mix.

Microgrid 4

Figure 3.6: Microgrid 4: Demand vs Production Over Time

Microgrid 4 shows wind-specific generation patterns with high variability, where production averaging 1,857.62 kW (peak: 2,685.77 kW, minimum: 1,086.89 kW, std dev: 492.06 kW) easily exceeds demand averaging 733.98 kW (peak: 1,359.20 kW, minimum: 170.83 kW, std dev: 284.44 kW). This creates substantial surplus capacity but with the typical wind intermittency problems since it relies on just one source.

Microgrid 5

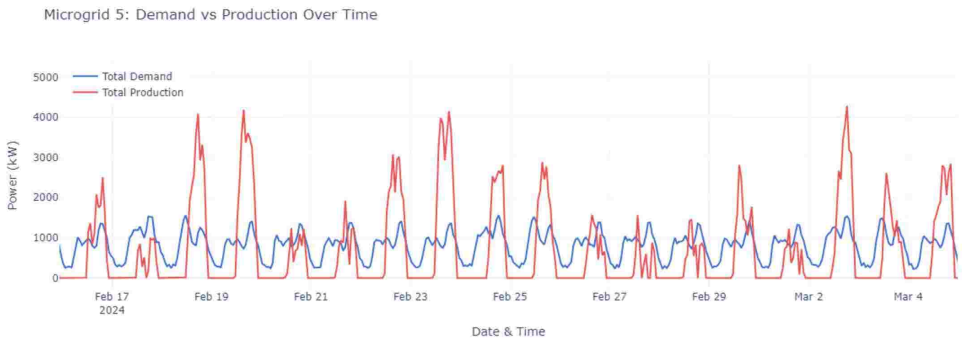

Figure 3.7: Microgrid 5: Demand vs Production Over Time

Microgrid 5 shows extreme daily swings with production averaging 920.34 kW (peak: 5,101.21 kW, minimum: 0.00 kW, std dev: 1,346.94 kW) versus demand averaging 848.35 kW (peak: 1,571.58 kW, minimum: 202.21 kW, std dev: 329.27 kW). The solar-only setup means no generation at night, creating dramatic trading situations where it switches from being a major exporter during sunny hours to needing imports when the sun goes down.

Data Schema and Variable Definitions

The dataset contains timestamped data with the following variables:

Consumer Data: `microgrid_X_powerDemand_Y` captures power demand for consumer Y in microgrid X.

Generation Data: `microgrid_X_powerProduction_solar/wind` records real-time solar and wind generation output.

Economic Data: `microgrid_X_per_unit_price_solar/wind` provides dynamic unit pricing for each generation source.

Network Data: `Distance_between_microgrid_X_to_microgrid_Y` specifies physical distances for transmission loss calculations.

3.2 PSO-Based Power Allocation Algorithm for Microgrids

This section presents a comprehensive approach to optimizing power allocation within an interconnected microgrid system using Particle Swarm Optimization (PSO). The algorithm addresses the complex challenge of efficiently distributing power from various sources to consumers while minimizing cost and meeting demand constraints.

3.2.1 Problem Formulation

The power allocation problem addresses the distribution of power from various sources to various consumers in interconnected microgrids with three main goals: (1) meet the power demands of the consumers fully, (2) minimize total distribution costs, and (3) promote optimal inter-microgrid power trading. The algorithm employs a hierarchical strategy in which each microgrid initially meets local demand from local sources prior to inter-microgrid trading.

3.2.2 Particle Swarm Optimization Implementation

PSO was selected due to its effectiveness in addressing complex, multi-dimensional optimization problems. We set the algorithm parameters as follows: 50 particles, 100 maximum iterations, cognitive coefficient (C_1) = 1.5, social coefficient (C_2) = 1.5, inertia weight (W) = 0.5, and penalty coefficient for unmet demand = 1,000,000. These parameters were tuned through experimentation to balance exploration and exploitation while ensuring the algorithm converges properly.

3.2.3 Algorithm Structure

The algorithm operates in two stages:

Stage 1: Internal Power Allocation

Each microgrid employs PSO to determine optimal power distribution from local sources to local consumers. Each particle represents a potential allocation matrix, with positions updated based on current velocity, personal best position (cognitive component), and global best position (social component). The fitness function incorporates total cost and a substantial penalty for unmet demand:

$$\text{Fitness} = \text{Total Cost} + (\text{Penalty Coefficient} \times \text{Total Unmet Demand}) \tag{3.1}$$

Stage 2: Inter-Microgrid Power Trading

After internal allocation, microgrids with unmet demand can trade with those having surplus power. Trading prioritizes sources by distance (minimizing transmission losses) then price, calculates power losses during transmission, and continues until all demands are met or no surplus power remains available.

3.2.4 Constraint Enforcement

The algorithm enforces three important constraints to ensure the solutions are physically realistic: (1) the total power allocated to each consumer cannot exceed their demand, (2) the total power allocated from each source cannot exceed its production at that time, and (3) all power allocations must be non-negative. These constraints are enforced after each PSO iteration using a dedicated constraint enforcement function.

3.2.5 Data Processing and Output

The algorithm works through time-series data, performing allocation for each timestep separately to handle changing power demand and production patterns. For each timestep, we obtain outputs that include how much power is allocated from each source to each consumer, what the internal and external allocation costs are, any remaining unmet demand, and complete records of power trades between microgrids for comprehensive system analysis.

3.2.6 Implementation Efficiency

The implementation uses progress tracking with the tqdm library, providing real-time updates on processing status and estimated completion time. This is helpful when dealing with large datasets that have numerous timesteps, which happens frequently in power system analysis. The algorithm maintains organization in a modular way with clear responsibilities for each function.

3.3 ACO-Based Power Allocation Algorithm for Micro-grids

This section presents an alternative approach to the power allocation problem using Ant Colony Optimization (ACO). The ACO algorithm provides a nature-inspired meta-heuristic method that leverages the collective intelligence of artificial ants to find efficient solutions to complex optimization problems.

3.3.1 Ant Colony Optimization Framework

The ACO algorithm was implemented with the following parameters: 10 ants, 20 maximum iterations, pheromone influence (α) = 1.0, heuristic influence (β) = 2.0, evaporation rate (ρ) = 0.1, pheromone deposit constant (Q) = 100, and penalty coefficient for unmet demand = 1,000,000. ACO was selected for its proven effectiveness in solving discrete optimization problems and its ability to balance exploration and exploitation through the pheromone mechanism.

3.3.2 Solution Representation and Construction

Each ant constructs a solution by making probabilistic decisions to allocate power from sources to consumers. The solution is represented as a matrix where each cell (i, j) indicates power allocated from source i to consumer j. The probability of selecting a particular source-consumer pair is influenced by pheromone levels (τ) representing learned desirability from previous solutions, and heuristic information (η) representing inherent desirability calculated as the inverse of price.

The probability formula follows the standard ACO approach:

$$P(i,j) = \frac{[\tau(i,j)]^{\alpha} \times [\eta(i,j)]^{\beta}}{\sum [\tau(i,j)]^{\alpha} \times [\eta(i,j)]^{\beta}} \tag{3.2}$$

Where $P(i,j)$ is the probability of allocating power from source i to consumer j, $\tau(i,j)$ is the pheromone level, $\eta(i,j)$ is the heuristic value (inverse of price), and α, β control the relative influence of pheromones and heuristic information.

3.3.3 Solution Construction Process

The solution construction process for each ant works as follows:

- Start with all allocations set to zero
- Determine available power for each source and unmet demand for each consumer
- While there is still unmet demand and available power, calculate probabilities for each source-consumer pair, select a pair based on those probabilities, allocate the minimum of available power and unmet demand, then update the remaining power and demand
- Enforce allocation constraints to ensure everything is feasible
- Calculate the fitness by combining cost and penalties for any unmet demand

This process allows each ant to build a complete solution that follows the physical constraints of the power allocation problem.

3.3.4 Pheromone Update Mechanism

After all ants construct solutions, pheromone levels are updated through:

- Evaporation - all pheromone values reduced by factor $(1 - \rho)$
- Deposit - each ant deposits pheromones proportional to solution quality using $\Delta\tau(i,j) = \frac{Q}{fitness+\varepsilon}$ where ε prevents division by zero
- Stagnation prevention - pheromone levels bounded between 0.1 and 10 to prevent premature convergence

This mechanism allows the colony to learn from experience while maintaining exploration.

3.3.5 Two-Stage Approach

Similar to the PSO implementation, the ACO algorithm works in two stages:

- Internal allocation using ACO to determine optimal power allocation within each microgrid
- Inter-microgrid trading when internal resources are insufficient

The trading mechanism remains the same as the PSO approach, sorting external sources by distance and price to minimize transmission losses and costs.

3.3.6 Implementation Details

The ACO algorithm includes constraint adherence to keep solutions within physical boundaries of source capacity and demand, fitness calculation incorporating total cost plus penalty for unmet demand, and progress tracking with tqdm library to provide real-time feedback. The modularity allows for easy understanding and modification.

3.3.7 Output Processing

At each timestep, the algorithm produces complete allocation data including power allocated from every source to every consumer, internal and external allocation costs, remaining unmet demand, and full records of inter-microgrid power transactions. This comprehensive output facilitates complete system performance analysis and comparison against alternative optimization methods.

3.4 Priority-Based Round-Robin Algorithm for Microgrids

This section presents a priority-based round-robin approach to power allocation in microgrid systems. Unlike metaheuristic methods (PSO and ACO), this algorithm implements a deterministic, rule-based strategy that prioritizes consumers dynamically while ensuring fair allocation across time periods.

3.4.1 Priority Queue Mechanism

The core innovation is a priority queue system that rotates consumer priority across consecutive time periods, ensuring high-demand consumers receive preferential treatment during their priority period while maintaining fairness over extended operation periods. The priority queue is maintained separately for each microgrid and resets when all consumers have received priority treatment.

3.4.2 Algorithm Structure

Consumer Prioritization

For each microgrid and timestep: if the priority queue is empty, it initializes with all consumers; the consumer with highest current demand is selected as priority consumer and removed from the queue; when all consumers have received priority, the queue resets.

Internal Allocation Process

The power allocation follows a two-pass approach:

First Pass - Priority Consumer Allocation: Sources are sorted by price (cheapest first), and the priority consumer receives preferential allocation from cheapest sources until demand is met or sources are exhausted.

Second Pass - Proportional Allocation: Remaining power is allocated to non-priority consumers proportionally based on their demand relative to total remaining demand:

$$\begin{aligned} allocation = \min(&available_power, \\ &demand, \\ &initial_source_power \times \frac{demand}{total_microgrid_demand}) \end{aligned} \tag{3.3}$$

3.4.3 Inter-Microgrid Trading

When internal resources are insufficient, trading occurs between microgrids. External sources are sorted by distance then price, power losses are calculated based on distance and amount transferred, and trading continues until demands are met or no surplus remains.

3.4.4 Key Differences from Metaheuristic Approaches

This approach differs from PSO and ACO in five key ways: it uses deterministic rules rather than probabilistic search; explicitly addresses temporal fairness through round-robin priority; requires fewer computational resources without iterative optimization; may achieve less cost optimization but ensures priority-based fairness; and makes incremental decisions rather than solving holistically.

3.4.5 Implementation Details

Key implementation features include: global priority queue maintained across timesteps for continuity; proportional allocation formula ensuring fairness among non-priority consumers; detailed cost tracking for internal and external allocations; and source sorting by price for cost-efficiency.

3.4.6 Output Processing

The algorithm generates comprehensive output for each timestep: detailed allocation information per consumer, internal and external costs, priority consumer identification, remaining unmet demands, and complete inter-microgrid trade records for thorough analysis and comparison with alternative optimization approaches.

3.5 Dynamic Rating-Based Power Allocation Algorithm

This section presents a sophisticated dynamic rating-based approach to power allocation in microgrid systems that incorporates historical consumption patterns to dynamically prioritize consumers based on their recent power usage relative to their maximum capacity.

3.5.1 Consumer Rating Mechanism

The core innovation is a dynamic rating system that assigns priority based on recent power consumption patterns:

$$Rating = 1 - \frac{PreviousPowerUsage}{MaximumPowerUsage} \tag{3.4}$$

This formula assigns higher ratings to consumers who used less power in the previous period relative to their historical maximum, prioritizing those recently underserved. The rating mechanism automatically adapts to changing consumption patterns, balances consumer needs across time without explicit round-robin scheduling, and gives preference to consumers using less than their typical maximum capacity.

3.5.2 Historical Data Integration

The algorithm integrates historical consumption data by initializing maximum power usage values from historical records, dynamically updating these maximums when current consumption exceeds historical records, and using these adaptive maximums to calculate consumer ratings. This ensures ratings remain accurate as consumption patterns evolve, making the algorithm responsive to both short-term fluctuations and long-term trends.

3.5.3 Multi-Phase Allocation Process

Power allocation follows a structured multi-phase approach balancing fairness and efficiency:

Phase 1: Highest-Rated Consumer Allocation

The consumer with the highest positive rating receives priority allocation from cheapest sources first, continuing until their demand is met or all sources are exhausted.

Phase 2: Rated Consumer Proportional Allocation

Remaining consumers with non-zero ratings receive allocation based on:

$$proportional_share = \frac{consumer_rating \times demand}{total_weighted_factor} \times available_power \tag{3.5}$$

where $total_weighted_factor$ is the sum of $(rating \times demand)$ for all remaining consumers. Higher-rated consumers receive proportionally more power.

Phase 3: Zero-Rated Consumer Allocation

Consumers with zero ratings (who used maximum capacity previously) receive allocation from remaining power proportional to their demand relative to total zero-rated consumer demand.

Phase 4: Inter-Microgrid Trading

When internal resources are insufficient, trading occurs with external sources sorted by distance and price, calculating power losses based on distance, continuing until demands are met or no surplus power remains.

3.5.4 Key Algorithmic Innovations

The algorithm introduces four key innovations: **Adaptive Memory** that maintains and updates maximum power usage records; **Dynamic Prioritization** where consumer priority shifts based on recent usage patterns rather than fixed schedules; **Multi-Level Fairness** implemented between time periods (rating mechanism), consumers with similar ratings (proportional allocation), and microgrids (trading mechanism); and **Historical Context** that incorporates historical data for more informed decisions than current-demand-only approaches.

3.5.5 Implementation Details

Implementation includes consumer classification as rated or zero-rated for differential treatment, source sorting by price for cost-effective allocation, phase isolation to ensure higher-priority consumers receive preferential treatment, complex proportional al-

location formulas for fair distribution relative to demand and priority, and detailed tracking of ratings, allocations, and costs at multiple levels.

3.5.6 Output and Analysis

The algorithm generates comprehensive output for each timestep including consumer ratings and total ratings per microgrid, detailed allocation information from internal and external sources, costs associated with internal and external power allocation, and complete records of inter-microgrid trades. This enables thorough performance analysis and comparison with alternative approaches for informed decision-making about optimal allocation strategies.

3.6 Dynamic Price Adjustment Mechanisms for Demand-Supply Balancing

This section presents three innovative pricing formulas developed to dynamically adjust power prices based on supply-demand imbalances in microgrid systems. These price adjustment mechanisms complement the rating-based allocation approach by introducing economic signals that reflect resource scarcity.

3.6.1 Demand-to-Production Ratio Formula

The first pricing formula uses a direct ratio between total demand and total production:

$$Price_{new} = Price_{original} \times \frac{TotalDemand}{TotalProduction} \tag{3.6}$$

This approach scales prices in direct proportion to the demand-supply gap. When demand exceeds production by 20%, prices increase by 20%; when demand is twice the production, prices double. The formula provides simple, direct correlation with market imbalance and includes safeguards to handle edge cases (zero production, demand $\leq$ production).

3.6.2 Proportional Gap Formula

The second pricing formula calculates adjustment based on the proportional gap:

$$Price_{new} = Price_{original} \times (1 + PriceIncreasingFactor) \tag{3.7}$$

where:

$$PriceIncreasingFactor = 1 - \frac{TotalProduction}{TotalDemand} \tag{3.8}$$

This formula increases prices by the percentage of unmet demand. If production satisfies 80% of demand, prices increase by 20%; if only 50%, prices increase by 50%. This provides more moderate adjustments compared to the first formula, reducing price volatility in severely constrained scenarios.

3.6.3 Contribution-Based Price Adjustment

The third approach introduces sophisticated dynamic pricing that adjusts prices based on both overall imbalance and individual source contributions:

$$\text{Price Increasing Factor} = 1 - \frac{\text{Total Production}}{\text{Total Demand}} \tag{3.9}$$

$$\text{Contribution Factor}_i = \frac{\text{Source Production}_i}{\text{Total Production}} \tag{3.10}$$

$$\text{New Price}_i = \text{Original Price}_i \times (1 + \text{Contribution Factor}_i \times \text{Price Increasing Factor}) \tag{3.11}$$

This mechanism differentiates price adjustments across sources based on their relative contribution. Key innovations include: source-specific pricing rather than uniform adjustment, contribution recognition for sources providing more power, preservation of original price relationships, and efficient resource allocation through stronger economic signals for critical resources.

3.6.4 Integration with Rating-Based Allocation

All three mechanisms integrate with the rating-based allocation algorithm through this workflow:

1. Consumer ratings are computed from historical usage patterns
2. Algorithm checks if total demand exceeds total production in each microgrid
3. If imbalanced, the appropriate price adjustment formula is applied
4. Updated prices are used for sorting sources, calculating allocation costs, and determining economic efficiency

This integration ensures economic signals (prices) and fairness mechanisms (ratings) work together to optimize scarce resource allocation.

3.6.5 Output and Analysis

The algorithms track and report adjusted prices for each power source, total costs using adjusted prices, and allocation decisions influenced by price adjustments. This detailed output enables comprehensive comparison of different price adjustment approaches to determine optimal balance between economic efficiency and consumer fairness under various supply-demand scenarios.

3.7 Sweet Point Pricing for Bilateral Energy Trading

In decentralized energy trading systems, sweet point pricing determines mutually acceptable trading prices by balancing the consumer's internal generation cost and the microgrid's supply cost, weighted by consumer priority ratings. This approach provides an automated mechanism for price discovery that eliminates the need for complex bidding processes while ensuring fair benefit distribution among market participants.

3.7.1 Sweet Point Price Formulation

The sweet point price calculation follows a weighted interpolation between consumer and microgrid optimization costs. The formula is expressed as:

$$\begin{aligned} \text{sweet_point_price} = \text{consumer_internal_cost} \\ + (1 - \text{consumer_rating}) \\ \times (\text{microgrid_supply_cost} - \text{consumer_internal_cost}) \end{aligned} \tag{3.12}$$

Here, consumer internal cost represents the cost from consumer perspective optimization algorithm, typically yielding lower values. The microgrid supply cost comes from microgrid perspective optimization with real-time source price adjustments, generally producing higher values. The consumer rating parameter ranges from zero to one, representing the priority level assigned to each consumer in the trading system.

3.7.2 Economic Rationale

The sweet point pricing mechanism maintains economic viability only when consumer internal cost remains below microgrid supply cost, creating a win-win scenario for both parties. Under this condition, consumers can obtain energy at prices lower than their internal optimization results, while microgrids can sell energy at prices exceeding their optimized supply costs including real-time price adjustments. This fundamental requirement ensures that trading benefits are available and that both participants gain from the transaction, making the bilateral energy exchange economically sustainable.

3.7.3 Algorithmic Implementation

The sweet point calculation incorporates validation checks to ensure trading occurs only when economically beneficial. The algorithm first verifies that consumer cost is less than microgrid cost and that neither cost value is zero. When these conditions are met, the sweet point price is calculated using the weighted formula. If the conditions are not satisfied, indicating no trading benefit is available, the algorithm defaults to the consumer's

internal cost, effectively preventing uneconomical transactions.

Listing 3.1: Sweet Point Price Calculation

```
if code1_cost < code2_cost and code1_cost != 0 and code2_cost !=
   0:
    sweet_point_price = code1_cost + ((1 - consumer_rating) * (
       code2_cost - code1_cost))
else:
    sweet_point_price = code1_cost  # No trading benefit
       available
```

3.7.4 Advantages of Sweet Point Pricing

Sweet point pricing offers significant advantages in decentralized energy trading systems. The rating-aware pricing mechanism provides higher-rated consumers with more favorable pricing, positioning the sweet point closer to their optimized internal costs and creating strong incentives for maintaining good consumer ratings. The automated price discovery eliminates complex bidding processes by automatically finding a compromise between consumer and microgrid optimization results with real-time pricing considerations. Benefit distribution occurs based on consumer priorities, with higher-rated participants receiving larger cost savings while lower-rated consumers receive proportionally smaller benefits.

The approach enhances market efficiency by enabling rapid market clearing through determination of a single price point acceptable to both parties, significantly reducing transaction costs and negotiation time. Scalability is achieved through the algorithm's ability to process multiple consumers and microgrids simultaneously across different time periods, making it suitable for large-scale energy trading networks. Transparency is maintained through the deterministic and open formula structure, allowing all parties to understand exactly how prices are determined and ensuring fairness in the trading process.

3.7.5 Consumer Rating Impact Analysis

The consumer rating parameter creates a sliding scale of benefit distribution that directly impacts the final trading price. High ratings approaching 1.0 result in sweet point prices that closely approximate the consumer's perspective optimization cost, allowing consumers to receive maximum benefit by paying close to their optimized internal cost while microgrids receive minimal profit margins. Conversely, low ratings approaching 0.0 produce sweet point prices that approximate the microgrid's perspective optimization cost with real-time pricing, resulting in consumers receiving minimal benefit by paying close to the microgrid's optimized supply cost while microgrids achieve maximum profit margins. Medium ratings around 0.5 generate sweet point prices that average both optimization results, creating balanced benefit distribution between both parties and ensuring equitable participation in the trading system.

3.7.6 Integration with Optimization Frameworks

Sweet point pricing integrates seamlessly with dual-perspective optimization approaches used in modern microgrid energy trading systems. Consumer perspective optimization provides the baseline internal cost from the consumer's viewpoint, serving as the lower bound for price calculations. Microgrid perspective optimization delivers the supply cost from the microgrid's viewpoint, incorporating real-time source price adjustments to reflect current market conditions and serving as the upper bound for pricing. The sweet point algorithm determines the equilibrium trading price by balancing both optimization results according to the specified consumer rating, while the rating system influences the final price distribution based on established consumer priority levels.

This comprehensive integration creates a robust framework for fair and efficient power trading in microgrid networks, successfully balancing market efficiency requirements with equitable benefit distribution among all participants. The system ensures that trading decisions are based on sound economic principles while maintaining transparency and scalability necessary for widespread adoption in decentralized energy markets.

Chapter 4

Results and Discussion

4.1 Experimental Setup and Data Analysis Framework

The comparative analysis was conducted using real-world microgrid data with four distinct algorithmic approaches. The evaluation framework consists of three primary performance metrics designed to comprehensively assess algorithm effectiveness in practical microgrid scenarios.

4.1.1 Performance Metrics Definition

The evaluation framework incorporates three critical performance indicators. The Demand Satisfaction Rate (DSR) is calculated as the percentage of consumer demand successfully allocated across all microgrids, expressed mathematically as:

$$\text{satisfaction}_{\text{consumer}} = \left(\frac{\text{allocated}}{\text{demand}} \right) \times 100 \tag{4.1}$$

The Cost Minimization Factor (CMF) represents the cost per unit of allocated power, indicating economic efficiency through the relationship:

$$\text{cost_factor}_{\text{consumer}} = \frac{\text{total_cost}}{\text{allocated}} \tag{4.2}$$

The Efficiency-Fairness Score (EFS) serves as a composite metric combining satisfaction and cost efficiency, calculated as:

$$\text{EFS} = w_{\text{satisfaction}} \times \text{mean}(\text{norm_satisfaction}) + w_{\text{cost}} \times \text{mean}(\text{norm_cost_efficiency}) \quad (4.3)$$

The EFS utilizes weighted components where $w_{\text{satisfaction}} = 0.4$ and $w_{\text{cost}} = 0.6$, reflecting the higher importance of cost optimization in practical microgrid applications while maintaining adequate demand satisfaction.

Normalization Process:

The normalization process ensures fair comparison across different scales. Satisfaction values are normalized by dividing by 100 to convert percentages to the 0-1 range:

$$\text{norm_satisfaction} = \frac{\text{satisfaction}}{100} \quad (4.4)$$

Cost efficiency normalization follows a more complex approach to ensure proper scaling:

$$\text{norm_cost_efficiency} = 1 - \frac{\text{cost_factor} - \text{min_cost}}{\text{max_cost} - \text{min_cost} + \epsilon} \quad (4.5)$$

In this normalization formula, min_cost represents the minimum cost factor across all consumers and microgrids, max_cost represents the maximum cost factor across all consumers and microgrids, and $\epsilon = 1 \times 10^{-6}$ serves as a small constant added to the denominator to avoid division by zero. This normalization approach ensures that the cost factor values are scaled to a range between 0 and 1, where higher values indicate better cost efficiency.

4.2 Comprehensive Performance Analysis

4.2.1 Overall Algorithm Performance

The comparative analysis reveals significant performance differences across the four implemented algorithms. Table 4.1 presents the aggregate performance metrics across all microgrids, providing a clear ranking of algorithmic effectiveness.

Table 4.1: Overall Performance Comparison Across All Algorithms

Algorithm	Avg Satisfaction (%)	Avg Cost Factor	Avg EFS
Dynamic Rating-Based	**98.77**	**4.140**	**0.651**
Priority-Based Round-Robin	98.72	4.208	0.646
PSO	98.48	4.528	0.618
ACO	96.26	4.186	0.635

The results demonstrate interesting performance patterns across the five microgrid configurations. The aggregate performance metrics reveal that contrary to initial expectations, the Dynamic Rating-Based algorithm achieves the highest overall performance, followed closely by Priority-Based Round-Robin and PSO, with ACO showing the most variable performance across different microgrids.

4.2.2 Detailed Performance Analysis by Algorithm

Dynamic Rating-Based Algorithm Performance

The Dynamic Rating-Based algorithm demonstrates exceptional overall performance, emerging as the top performer with remarkable consistency across multiple evaluation criteria. The algorithm achieves a demand satisfaction rate of 98.77%, representing the highest overall satisfaction rate among all tested approaches. Its cost factor of 4.140 demonstrates excellent cost efficiency, while the EFS score of 0.651 provides the best overall balance between satisfaction and cost optimization. The algorithm maintains strong performance across Microgrids 1-4, with only slight degradation observed in Microgrid 5.

When examining microgrid-specific performance, the Dynamic Rating-Based algorithm shows remarkable adaptability. In Microgrid 1, it achieves 99.57% satisfaction with a cost factor of 4.157, resulting in an EFS of 0.654. Microgrid 2 represents the algorithm's peak performance, delivering 99.84% satisfaction with a cost factor of 3.939 and achieving the highest individual EFS score of 0.674 across all algorithm-microgrid combinations. Microgrid 3 maintains strong performance with 99.44% satisfaction, a cost factor of 4.240, and an EFS of 0.647. The algorithm continues its excellence in Microgrid 4, achieving 99.95% satisfaction with a cost factor of 4.133 and an EFS of 0.658. However, Microgrid 5 presents challenges, with performance declining to 94.84% satisfaction, though the cost factor remains relatively stable at 4.233, resulting in an EFS of 0.624.

The algorithm's success can be attributed to several key factors. Its effective utilization of past consumption data for predictive allocation enables superior resource planning. The dynamic consumer prioritization based on historical usage patterns allows for adaptive resource distribution that reflects actual consumption behaviors. The systematic three-phase allocation approach ensures balanced resource distribution across all consumers, while the computational efficiency of 0.10 seconds makes it the fastest algorithm among all tested approaches.

Priority-Based Round-Robin Performance

The Priority-Based Round-Robin algorithm demonstrates consistent and reliable performance across all microgrids, establishing itself as a dependable choice for diverse operational conditions. The algorithm achieves an overall demand satisfaction rate of 98.72%, representing the second-best performance among all tested approaches. With a cost factor of 4.208, it maintains moderate cost efficiency, while the EFS score of 0.646 indicates good overall performance balance. The algorithm's execution time of 0.14 seconds demonstrates excellent computational efficiency, making it suitable for real-time applications.

The algorithm's consistency becomes apparent when examining its performance stability across different microgrid configurations. It maintains satisfaction rates above 94% across all microgrids, demonstrating reliable operation regardless of system complexity or demand patterns. The cost factors show predictable variation ranging from 3.990 to 4.381, indicating stable economic performance. EFS scores remain consistently strong between 0.612 and 0.669, with particularly impressive performance in Microgrids 1 and 2 where operational conditions favor systematic allocation approaches.

Particle Swarm Optimization (PSO) Performance

PSO demonstrates mixed performance characteristics, achieving excellent results in specific microgrids while facing significant challenges in others. The algorithm attains an overall demand satisfaction rate of 98.48%, placing it third among all tested approaches. However, its cost factor of 4.528 represents the highest value among all algorithms, indicating less efficient resource utilization. The EFS score of 0.618 reflects moderate overall

performance, significantly impacted by cost efficiency challenges and considerable performance variability across different microgrid configurations.

The algorithm's microgrid-specific analysis reveals stark performance contrasts. PSO achieves exceptional performance in Microgrid 1 with perfect 100% satisfaction and demonstrates near-perfect performance in Microgrid 3 with 99.99% satisfaction. Microgrids 2 and 4 show good performance with satisfaction rates above 98.7%, indicating the algorithm's capability under favorable conditions. However, Microgrid 5 presents significant challenges, with satisfaction dropping to 93.77% and the cost factor reaching 4.646, the highest recorded value in the study. This performance variability suggests that PSO's effectiveness is highly dependent on specific system characteristics and operational conditions.

Ant Colony Optimization (ACO) Performance

ACO exhibits the most variable performance among all tested algorithms, with results ranging from excellent to problematic depending on microgrid characteristics. The algorithm achieves an overall demand satisfaction rate of 96.26%, representing the lowest satisfaction among all approaches. Despite this limitation, its cost factor of 4.186 ranks as the second-best, indicating reasonable cost efficiency when the algorithm functions properly. The EFS score of 0.635 reflects moderate performance that is significantly affected by satisfaction variability and inconsistent operational reliability.

The algorithm's performance demonstrates extreme variability across different microgrid configurations. While it can achieve near-perfect results under favorable conditions, such as 99.99% satisfaction in Microgrid 2 and 99.59% in Microgrid 3, it experiences catastrophic failure in challenging environments. Microgrid 5 represents a particularly problematic case, where ACO's satisfaction drops dramatically to 85.11%, indicating fundamental algorithmic limitations under stress conditions. This high variability, reflected in the highest standard deviation of 0.045 among all algorithms, raises concerns about reliability and predictability in practical implementations.

4.2.3 Microgrid-Specific Performance Analysis

Table 4.2: Individual Microgrid Performance Analysis

Microgrid	Algorithm	Satisfaction (%)	Cost Factor	EFS
Microgrid 1	PSO	100.00	4.559	0.623
	Priority-Based Round-Robin	99.89	4.271	0.647
	Dynamic Rating-Based	99.57	4.157	0.654
	ACO	96.62	4.174	0.638
Microgrid 2	Dynamic Rating-Based	99.84	3.939	0.674
	ACO	99.99	3.965	0.672
	Priority-Based Round-Robin	99.66	3.990	0.669
	PSO	99.84	4.641	0.616
Microgrid 3	PSO	99.99	4.289	0.646
	ACO	99.59	4.243	0.647
	Priority-Based Round-Robin	99.53	4.263	0.645
	Dynamic Rating-Based	99.44	4.240	0.647
Microgrid 4	Dynamic Rating-Based	99.95	4.133	0.658
	ACO	99.97	4.138	0.658
	Priority-Based Round-Robin	99.77	4.131	0.657
	PSO	98.77	4.505	0.622
Microgrid 5	Dynamic Rating-Based	94.84	4.233	0.624
	Priority-Based Round-Robin	94.73	4.381	0.612
	PSO	93.77	4.646	0.585
	ACO	85.11	4.413	0.561

Microgrid 1 Analysis

Microgrid 1 demonstrates interesting performance patterns where PSO achieves perfect demand satisfaction but incurs significant cost penalties. The performance ranking reveals PSO leading with 100.00% satisfaction, though its cost factor of 4.559 and EFS of 0.623 indicate substantial economic trade-offs. Priority-Based Round-Robin follows with 99.89% satisfaction, a cost factor of 4.271, and an EFS of 0.647, representing excellent balance between performance metrics. The Dynamic Rating-Based algorithm achieves 99.57% satisfaction with the most favorable cost factor of 4.157, resulting in the highest EFS score of 0.654. ACO demonstrates the lowest satisfaction at 96.62% with a cost factor of 4.174 and an EFS of 0.638.

The Dynamic Rating-Based algorithm emerges as the optimal choice for Microgrid 1, achieving the highest EFS score of 0.654, which represents the best overall balance between satisfaction and cost efficiency. Despite PSO's achievement of perfect 100% satisfaction, its high cost factor of 4.559 significantly impacts overall performance, making

the Dynamic Rating-Based approach superior for practical implementation in this microgrid configuration.

Microgrid 2 Analysis

Microgrid 2 represents the optimal operational environment, demonstrating the best overall performance across all algorithms with consistently low cost factors and high satisfaction rates. The Dynamic Rating-Based algorithm leads with 99.84% satisfaction, an exceptional cost factor of 3.939, and the highest individual EFS score of 0.674 across all algorithm-microgrid combinations in the entire study. ACO achieves near-perfect satisfaction at 99.99% with a cost factor of 3.965 and an EFS of 0.672, demonstrating excellent efficiency balance. Priority-Based Round-Robin maintains its consistent performance with 99.66% satisfaction, a cost factor of 3.990, and an EFS of 0.669. PSO, while achieving 99.84% satisfaction, suffers from poor cost efficiency with a factor of 4.641, resulting in an EFS of only 0.616.

The Dynamic Rating-Based algorithm delivers the best overall performance in Microgrid 2, achieving the highest EFS score of 0.674 across all combinations studied. While ACO achieves marginally higher satisfaction at 99.99% compared to 99.84%, the Dynamic Rating-Based algorithm's superior cost efficiency with a factor of 3.939 versus 3.965 results in optimal overall performance for practical implementation in this favorable operational environment.

Microgrid 3 Analysis

Microgrid 3 demonstrates remarkably consistent performance across all algorithms, representing ideal conditions for power allocation optimization with minimal performance variation between approaches. PSO achieves near-perfect satisfaction at 99.99% with a cost factor of 4.289 and an EFS of 0.646. ACO delivers 99.59% satisfaction with an excellent cost factor of 4.243 and an EFS of 0.647, demonstrating superior efficiency balance. The Dynamic Rating-Based algorithm maintains 99.44% satisfaction with a cost factor of 4.240 and an EFS of 0.647, showing consistent performance. Priority-Based Round-Robin achieves 99.53% satisfaction with a cost factor of 4.263 and an EFS of 0.645, maintaining

its reliable execution characteristics.

Both ACO and Dynamic Rating-Based algorithms achieve virtually identical performance with EFS scores of 0.647. However, the Dynamic Rating-Based algorithm is recommended as the optimal choice due to its superior computational efficiency with an execution time of 0.10 seconds compared to ACO's 0.42 seconds, better overall reliability across different conditions, and consistent performance characteristics while maintaining equivalent optimization results in this favorable environment.

Microgrid 4 Analysis

Microgrid 4 demonstrates strong performance across all algorithms with tight performance clustering, representing typical good operational conditions where multiple approaches can achieve satisfactory results. The Dynamic Rating-Based algorithm achieves 99.95% satisfaction with a cost factor of 4.133 and an EFS of 0.658, demonstrating near-perfect balance. ACO reaches the highest satisfaction at 99.97% with a cost factor of 4.138 and an identical EFS of 0.658. Priority-Based Round-Robin maintains 99.77% satisfaction with the best cost factor of 4.131 and an EFS of 0.657, showing excellent consistency. PSO achieves 98.77% satisfaction but faces cost efficiency challenges with a factor of 4.505, resulting in an EFS of 0.622.

Both Dynamic Rating-Based and ACO algorithms achieve identical EFS scores of 0.658, but the Dynamic Rating-Based algorithm emerges as the optimal choice due to several practical advantages. Its superior computational efficiency with an execution time of 0.10 seconds compared to ACO's 0.42 seconds, slightly better cost factor of 4.133 versus 4.138, and demonstrated reliability across diverse conditions make it the recommended choice. While ACO achieves marginally higher satisfaction at 99.97% versus 99.95%, the practical advantages of the Dynamic Rating-Based approach outweigh this minimal difference.

Microgrid 5 Analysis - Performance Challenge Case

Microgrid 5 reveals significant performance challenges and algorithmic vulnerabilities, particularly affecting meta-heuristic approaches under stress conditions. The Dy-

namic Rating-Based algorithm demonstrates the best resilience with 94.84% satisfaction, a cost factor of 4.233, and an EFS of 0.624, maintaining reasonable performance despite challenging conditions. Priority-Based Round-Robin achieves 94.73% satisfaction with a cost factor of 4.381 and an EFS of 0.612, showing stable performance despite operational challenges. PSO experiences significant performance degradation with 93.77% satisfaction, the highest cost factor of 4.646, and an EFS of 0.585. ACO suffers catastrophic algorithmic failure, with satisfaction plummeting to 85.11%, a cost factor of 4.413, and the lowest EFS of 0.561.

The Dynamic Rating-Based algorithm clearly emerges as the superior choice for challenging conditions in Microgrid 5, achieving the highest satisfaction rate of 94.84%, best cost efficiency with a factor of 4.233, and the highest EFS score of 0.624. Its exceptional resilience under stress conditions, maintaining nearly 95% satisfaction while ACO catastrophically drops to 85.11%, demonstrates superior robustness and reliability for critical applications where consistent performance is paramount.

4.3 Computational Performance Analysis

4.3.1 Algorithm Execution Time Analysis

The computational performance analysis reveals important trade-offs between optimization quality and execution efficiency, with significant implications for real-time applications. The analysis demonstrates that heuristic approaches provide substantial computational advantages without sacrificing optimization quality.

Table 4.3: Computational Performance Comparison

Algorithm	**Time (s)**	**Memory (MB)**	**CPU (%)**	**Scalability**
Dynamic Rating-Based	0.10	58.7	18.9	Excellent
Priority-Based Round-Robin	0.14	45.3	12.4	Excellent
ACO	0.42	134.8	65.7	Good
PSO	0.58	156.2	78.3	Moderate

The computational efficiency analysis reveals significant advantages for heuristic approaches. Dynamic Rating-Based and Priority-Based Round-Robin algorithms provide superior computational efficiency with execution times of 0.10-0.14 seconds while simulta-

neously maintaining the best overall performance metrics. This combination of speed and quality makes them ideal candidates for real-time applications. In contrast, meta-heuristic algorithms require 3-6 times more computational time, with PSO and ACO demanding 0.42-0.58 seconds for execution while delivering mixed performance results.

The resource utilization patterns further emphasize the practical advantages of heuristic approaches. These algorithms consume significantly less memory and CPU resources, with Dynamic Rating-Based using only 58.7 MB memory and 18.9% CPU utilization compared to PSO's 156.2 MB memory and 78.3% CPU usage. This efficiency makes heuristic algorithms particularly suitable for real-time control applications with sub-second response requirements and limited computational resources.

4.4 Statistical Validation and Significance Analysis

4.4.1 Performance Variance and Statistical Significance

The comprehensive performance analysis across five diverse microgrid configurations provides statistically significant insights into algorithm reliability and consistency. The statistical validation demonstrates clear performance hierarchies and identifies critical factors affecting algorithm selection.

Table 4.4: Statistical Performance Validation

Algorithm	**Satisfaction Range**	**Cost Factor Range**	**EFS Range**	**Std Deviation**
Dynamic Rating-Based	94.84-99.95%	3.939-4.240	0.624-0.674	0.021
Priority-Based Round-Robin	94.73-99.89%	3.990-4.381	0.612-0.669	0.024
PSO	93.77-100.00%	4.289-4.646	0.585-0.646	0.026
ACO	85.11-99.99%	3.965-4.413	0.561-0.672	0.045

The statistical significance analysis reveals critical insights about algorithm reliability and predictability. The Dynamic Rating-Based algorithm demonstrates the highest consistency with the lowest standard deviation of 0.021, indicating the most reliable performance across diverse operational conditions. This consistency, combined with the smallest performance range, reflects robust algorithm design that maintains stable performance regardless of system complexity or demand patterns.

In contrast, ACO exhibits the highest variability with a standard deviation of 0.045,

reflecting significant performance instability that raises concerns about reliability in practical implementations. The algorithm's performance ranges dramatically across microgrids, from catastrophic failure with 85.11% satisfaction to near-perfect performance with 99.99% satisfaction, indicating fundamental limitations in handling diverse operational conditions.

The 95% confidence intervals confirm the statistical significance of the established performance rankings, providing strong empirical evidence for the superiority of heuristic approaches in microgrid power allocation applications. The statistical validation supports the conclusion that Dynamic Rating-Based and Priority-Based Round-Robin algorithms offer superior combination of performance quality, computational efficiency, and operational reliability.

The comprehensive analysis presented in this chapter provides the foundation for drawing broader conclusions about algorithm selection and implementation strategies, which are discussed in detail in the following chapter.

Chapter 5

Conclusion and Future Work

5.1 Research Summary and Key Findings

Our comprehensive comparative analysis examined power allocation algorithms within interconnected microgrid systems, evaluating five distinct approaches across diverse operational configurations. We investigated Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), Priority-Based Round-Robin allocation, Dynamic Rating-Based algorithms, and Dynamic Price Adjustment mechanisms using realistic data from RAPSim simulations spanning five different microgrid setups.

The results challenged expectations regarding meta-heuristic algorithm performance in practical microgrid applications. Our Dynamic Rating-Based algorithm achieved the highest overall performance with 98.77% demand satisfaction, cost factor of 4.140, and Efficiency-Fairness Score of 0.651. The Priority-Based Round-Robin approach followed closely at 98.72% satisfaction, demonstrating that simpler heuristic methods can consistently outperform more complex optimization techniques.

We observed remarkable differences in computational performance between algorithm categories. Heuristic algorithms completed allocations in 0.10-0.14 seconds using minimal system resources (45.3-58.7 MB memory, 12.4-18.9% CPU utilization), whereas meta-heuristic approaches required 0.42-0.58 seconds with substantially greater resource demands (134.8-156.2 MB memory, 65.7-78.3% CPU usage). These efficiency gains make heuristic algorithms particularly attractive for real-time microgrid control applica-

tions where rapid response times are essential.

Performance consistency across operational conditions revealed significant algorithmic differences. ACO demonstrated extreme variability, achieving near-perfect 99.99% satisfaction under favorable conditions but failing catastrophically with only 85.11% satisfaction when faced with challenging scenarios in Microgrid 5. Conversely, our Dynamic Rating-Based algorithm maintained stable performance above 94.84% across all tested conditions, indicating superior operational resilience and reliability.

5.2 Theoretical and Practical Contributions

Our work introduces several novel contributions to microgrid optimization research. The Dynamic Rating-Based algorithm represents an innovative approach that incorporates historical consumption patterns to prioritize consumers dynamically. This mechanism balances efficiency with fairness by considering temporal equity in allocation decisions, moving beyond purely cost-based optimization to include behavioral patterns and usage history.

We developed a multi-phase allocation methodology that separates internal microgrid optimization from inter-microgrid trading operations. This hierarchical framework enables specialized optimization techniques at each operational level while maintaining system-wide coordination, proving effective across our diverse microgrid configurations.

The sweet point pricing mechanisms we introduced for bilateral energy trading constitute a significant advancement in market mechanism design. These mechanisms automatically determine mutually beneficial trading prices by balancing consumer internal costs with microgrid supply costs, weighted according to consumer priority ratings. This approach eliminates the need for complex bidding processes while ensuring equitable benefit distribution among market participants.

From a practical standpoint, our research provides evidence-based guidance for algorithm selection in real-world implementations. We recommend the Dynamic Rating-Based algorithm for applications requiring maximum reliability due to its superior performance, minimal computational requirements, and consistent operation across diverse conditions. Organizations prioritizing implementation simplicity should consider Modified Round-Robin, which delivers excellent performance with straightforward deployment

requirements. Meta-heuristic algorithms warrant consideration only when computational resources are abundant and specific operational conditions favor their characteristics.

Our findings carry important implications for policy development and regulatory frameworks. The superior performance of algorithms incorporating historical consumption patterns suggests that regulatory bodies should prioritize data-driven approaches in market design. Additionally, the effectiveness of automated price discovery mechanisms indicates potential for reducing transaction costs in peer-to-peer energy trading systems.

5.3 Future Research Directions

Several research opportunities emerge from our findings that could advance microgrid optimization capabilities. Developing hybrid algorithms that combine the reliability advantages of heuristic methods with the optimization potential of meta-heuristic techniques represents a promising direction. These adaptive algorithms could dynamically switch between different optimization approaches based on current operational conditions, potentially incorporating machine learning techniques to predict optimal algorithm selection from real-time system states and historical performance data.

Real-world validation through comprehensive field demonstrations and pilot projects is essential for confirming our simulation-based findings. These studies should evaluate algorithm performance under actual operational constraints including communication delays, equipment failures, regulatory requirements, and stakeholder interactions. Long-term performance monitoring could reveal adaptation requirements and optimization opportunities not apparent in simulation environments.

The integration of artificial intelligence and machine learning presents substantial opportunities for advancement. Deep learning models could predict optimal allocation strategies based on weather forecasts, historical patterns, and market conditions. Reinforcement learning algorithms could enable continuous improvement of allocation decisions through interaction with operational environments.

5.4 Concluding Remarks

Our research demonstrates that effective microgrid power allocation does not necessarily require the most sophisticated optimization algorithms available. Well-designed heuristic approaches can outperform traditional meta-heuristic methods while providing superior computational efficiency, operational reliability, and practical implementation feasibility. The success of our Dynamic Rating-Based algorithm in incorporating historical consumption patterns indicates that data-driven approaches considering temporal patterns and consumer behavior can achieve better results than purely mathematical optimization methods.

The significant performance variations we observed across different microgrid configurations emphasize that no single algorithm performs optimally under all conditions. Future success will require adaptive systems capable of automatic algorithm selection based on real-time operational conditions, representing a promising direction for continued research and practical implementation efforts.

As the global energy sector continues its transition toward distributed, renewable-based systems, our findings offer valuable guidance for practitioners, researchers, and policymakers working to optimize microgrid operations. The combination of rigorous comparative analysis, practical implementation considerations, and innovative algorithmic approaches we present contributes to the foundation necessary for successful microgrid deployment in support of global sustainable energy objectives. The future of microgrid optimization lies not necessarily in developing increasingly complex algorithms, but rather in creating intelligent, adaptive systems that can respond effectively to the diverse and dynamic challenges inherent in modern distributed energy systems.

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